NOVEL TECHNIQUE OF SIZING THE STAND-ALONE PHOTOVOLTAIC SYSTEMS USING THE RADIAL BASIS FUNCTION NEURAL NETWORKS: APPLICATION IN ISOLATED SITES

A.MELLIT M.BENGHANME A. HADJ ARAB A.GUESSOUM

UNIVERSITY OF SCIENCES TECHNOLOGY HOUARI BOUMEDIENE (USTHB), FACULTY OF ELECTRICAL ENGINEERING, EL-ALIA, P.O.BOX 32. ALGIERS 16111 ALGERIA
PHONE/FAX: (213) 21 21 82 14
mellit_adel2001@yahoo.fr ,
m.benghanem@caramail.com

DEVELOPMENT CENTER OF RENEWABLE ENERGY (CDER), P.O.BOX 62, BOUZARÉAH, ALGIERS 16000, ALGERIA
hadjarab@hotmail.com

MINISTRY FOR THE HIGHER EDUCATION AND SCIENTIFIC RESEARCH, ALGIERS, ALGERIA
guessouma@hotmail.com

ABSTRACT

The objective of this work is to investigate the Radial Basis Function Neural Networks (RBFN) to identifying and modeling the optimal sizing couples of stand-alone photovoltaic (PV) system using a minimum of input data, These optimal couples allow to the users of stand-alone PV systems to determine the number of solar panel modules and storage batteries necessary to satisfy a given consumption. The advantage of this model is to estimate of the sizing PV system in any site in Algeria particularly in isolated sites, where the global solar radiation data is not always available. A RBFN has been trained by using 200 known sizing couples data corresponding to 200 locations. In this way, it was trained to accept and even handle a number of unusual case, known sizing couples were subsequently used to investigate the accuracy of prediction the training of the RBFN model was performed with adequate accuracy. Subsequently, the unknown validation sizing couples set produced very set accurate predictions with the correlation coefficient between the actual and the RBFN model identified data of 98% was obtained. This result indicates that the proposed method can be successfully used for estimating of optimal sizing couples of PV systems for any locations in Algeria, but the methodology can be generalized using different locations in the world.

1. INTRODUCTION

The design method is applied to areas all over the Algeria territory. The design of PV system depends on the location of these sites, the diversely of Algerian sites comes mainly from the influence of the sea and the latitude an altitude variations, the radiation at the regions near to the sea is influenced by the seasons or the zones of north Algeria are more sky-covered then those of the south. The estimate of the sizing couples PV system is very useful to conceive an optimal and economic stand-alone PV system. Several studies were elaborated on the performance of PV systems [1,2] for an optimal sizing. These methods are based on the energy balance to express the capacity storage and the output of PV systems, other more recent methods estimates the performance of PV systems while being based on the concept of Loss of Load Probability (LLP), defined as the ratio between the energy deficit and the energy demands both on the load [3,4,5].

$$LLP = \frac{\int_t Energy \quad deficit}{\int_t Energy \quad demand} \qquad (1)$$

Neural networks are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems, they can be trained to predict results from examples, and are fault tolerant in the sense that they are able to handle noisy and incomplete data, they are able to deal with non-linear problems, and once trained can perform prediction at very high speed. The power of neural network in modeling complex mapping and in system identification has been demonstrated. This method encouraged many researchers to explore the possibility of using neural network models in real world applications such as in control systems, classification, image processing and modeling complex process transformations.

Radial basis function networks become very popular due to several important advantages over traditional Multi-Layer Perceptrons (MLP) [6,7]:

- Locality of radial basis function feature extraction in hidden neurons, that allows usage of clustering algorithms and independent tuning of RBFN parameters.
- Sufficiency of one layer of non-linear elements for establishing arbitrary input-output mapping
- Solution of clustering problem can be performed independently from the weight in output layers
- RBFN output in scarcely trained areas of input space is not random, but depends on the density of the pairs in training data set [8].

These proprieties lead to potentially quicker learning in comparison to multi-layer perceptrons trained by Back-Propagation (BP). In some extent, RBFNs allow us to actualize a classical idea about training layer by layer.

The aim of this study is to investigate the suitability of the RBFN as a tool for the estimation of the optimal sizing couples of stand-alone PV systems in order to improve the results obtained in [9]. These couples allow to the users PV-system to determine the PV-array area and the storage capacity of the batteries necessary to satisfy a given consumption. The trained network could then be used as a design tool for estimating the performance of PV systems.

2. DATABASE OF DAILY GLOBAL SOLAR RADIATION

The sizing of the PV systems requires the knowledge of one of the components of solar beam known as daily of global solar radiation data measured by stations meteorological. However, these data are not always available because of the few weather stations in Algeria. Because of that, these were collected from data measurement system using a network configuration [10] and Markov Transition Matrices (MTM) approach [11]. As an example, figure 1 shows the daily values of global solar radiation data for four sites.

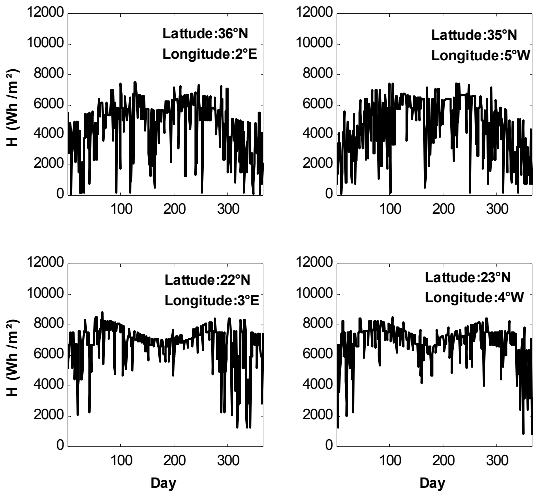

Fig. 1 Daily values of inclined global solar radiation data for samples sites

3. SIZING OF STAND-ALONE PHOTOVOLTAIC SYSTEM

The size of PV-system (figure 2) is a general concept including the sizing of PV-array and the accumulator. A useful definition of such dimensions relates to the load: In daily basis, the PV-array capacity (C_A) is defined as the ratio between mean PV-array energy production and the mean load energy demand, the storage capacity (C_S) is defined as the maximum energy that can be taken out from accumulator divided by the mean energy demand [12], so:

$$C_A = \frac{\eta_G A_G H}{L} \quad and \quad C_S = \frac{C_U}{L} \tag{2}$$

Where A_G is the PV-array area, η_g is the PV-array efficiency, H is the mean daily irradiation on the PV-array, L is the mean daily energy consumption, C_S is the storage capacity and C_U is the useful accumulator capacity. Note that C_A depends on the meteorological conditions of the location. That means that the same PV-array for the same load can be 'large' in one site and 'small' in another site with lower solar radiation.

The task of sizing a PV-system consists of finding the better trade-off between cost and reliability. Very often, the reliability is a priori requirement from the user, and the PV engineer problem is formulated as follows: which pair of C_A and C_S values leads to a given LLP value at the minimum cost?

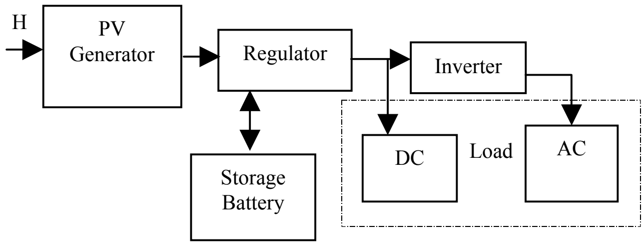

Fig. 2 Diagram block of simplified stand-alone PV system

4. RADIAL BASIS FUNCTION NETWORKS

Artificial neural network models represent a new method in system prediction. ANNs operate like a "black box" model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way a non-linear regression might perform. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. Although several network architectures and training algorithm are available, the Multi-Layer feed-forward neural network trained by the BP method is so far of one of the most popular. Many different types of ANN's, exist: single layer perceptron, multi-layer perceptron, the Hopfiled net, the Boltzman machine, the Hamming net, the classifier net and Kohonen's Sef-organization maps [13]. Each type of ANN exhibits its own architecture and learning algorithm. The ANN computation can be divided in two phases: learning phase and testing phase. The learning phase for forms an iterative updating of the synaptic weights based upon the error BP algorithm [14]. Mathematically, the function of the processing elements can be expressed as:

$$u(x,w) = \sum_{i=1}^{n} w_i x_i + b \tag{3}$$

Where b is the bias value, w_i is the synaptic weights, x_i is the input data. The value state of the node is determined by applying the activation function *f*. For our implementation, we have selected the logistic activation function:

$$f(u) = \frac{1}{(1+e^{-\lambda u})} \tag{4}$$

Where λ determine the steepness of the transition region.

The RBFN (figure 3) have a same structure as the MLP having only one hidden layer, the RBF is applied to the hidden layer [14-15] it is chosen as being Gaussian defined by its average m and its σ^2 variance, the output layer can be linear or non-linear function. The determination of the network parameters has the same procedure as the MLP [14], it is also a universal approximator [16]. That is to say a vector x having i components x_j formed the input layer of the RBF and that is to say a hidden layer contained h neurons and output layer, the output layer is given by:

$$Y = \sum_{i=1}^{h} w_i \exp\left(0.5 \frac{\sum_{j=1}^{k} (x_j - m_{ij})(x_j - m_{ij})}{\sigma_i^2} \right) \tag{5}$$

Where $m_i=(m_{i1},m_{i2},\ldots\ldots,m_{ik})$ is the vector average of the hidden neurone i, and which the element m_{ij} is the weight between input j and the hidden neurone i . σ^2 is the variance from the hidden neurone i and w_i is the weight binding the hidden neurone i to the output layer. Determination of the parameters m_{ij}, σ_i, and w_i is done by using the PB algorithm. The aim is to minimize the error (E) define by:

$$E=\sum_{i=1}^{N} e_i \tag{6}$$

Where N is the number of examples, e_i is the error between measured and estimated data.

$$w_{i,k+1}=w_{i,k}+\nu_1\sum_{l=1}^{N} e_{l,k}\, f\left(\|D\|^2\right) \tag{7}$$

$$\sigma_{i,k+1}=\sigma_{i,k}+\mu_3\, w_{i,k}\sum_{l=1}^{N} e_{l,k}\, f'\left(\|D\|^2\right) D D_T \tag{8}$$

$$m_{i,k+1}=m_{i,k}+2\mu_2\, w_{i,k}\sum_{l=1}^{N} e_{l,k}\, f'\left(\|D\|^2\right)\sigma_{i,j} D \tag{9}$$

Where $D=x_l-m_{i,k}$, μ_1, μ_2 and μ_3 are the learning rate.

In order to accelerate the convergence of the processes we used an adaptive method for fast BP algorithm is proposed in [17]. To speed up the learning process, we take advantage of new accelerating techniques of BP. Among these techniques, we choose the RPROP algorithm that is a direct adaptive method for faster BP learning. To overcome the disadvantages of classical BP, RPROP performs a local adaptation of weight update according to the behavior of the error function.

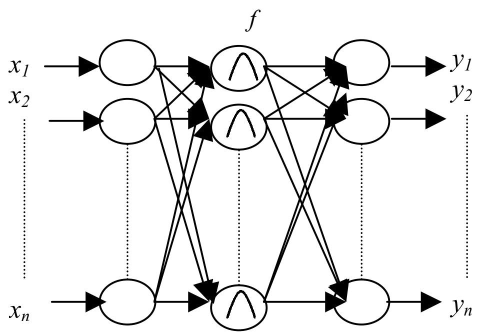

Fig. 3.The neural network architecture employed

5. DEVELOPED MODEL

Our methodology consists to calculate the various couples (C_A, C_S) corresponding at 200 sites (see figure 4), for this, we used the numerical method [12]. Next, we calculate the optimal couples (C_{AOP}, C_{SOP}) based on analytical cost (table 1). In this case database of optimal sizing couples is formed. Figure 5 shows the diagram block of developed model. The total of 200 patterns has been calculated for optimal couple sizing (C_{AOP}, C_{SOP}) as described above. From this set 184 patterns were used for the training of the network and 16 were used as for testing and validation for the model. The architecture that gave the best results is shown in figure 3. which has two neurons in the input layer and two neurons in the output layer. However, the number of the neurons in the hidden layer must be adjusted during the learning phase, so that the network can be trained efficiently. Developed model can be generating the optimal sizing couple from only the geographical coordinate. These couples allow calculating the PV-array area (A_{PV}) and the useful accumulator capacity (C_U).

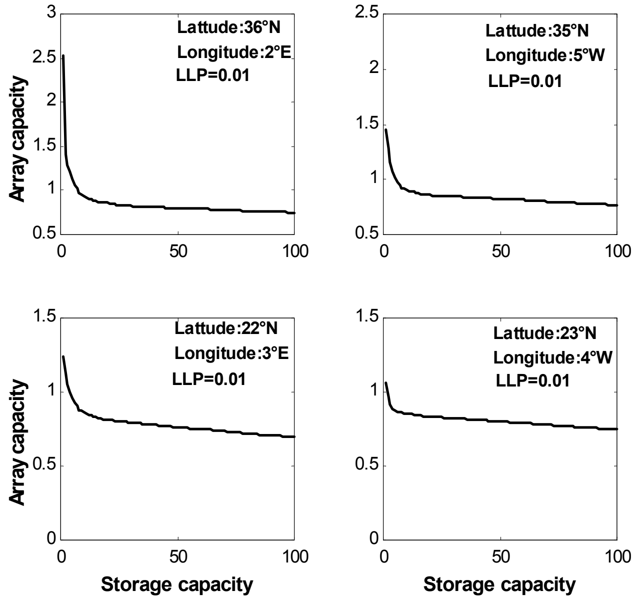

Fig.4. Iso-reliability curves

TABLE. 1. OPTIMAL SIZING COUPLES

Sites		Optimal sizing couples LLP=1%, L=1000Wh/day	
Latitude (Deg.)	Longitude (Deg.)	C_{AOP}	C_{SOP}
36	2	2.202	1.95
35	5	1.115	1.89
22	3	0.642	0.75
23	4	0.631	0.76

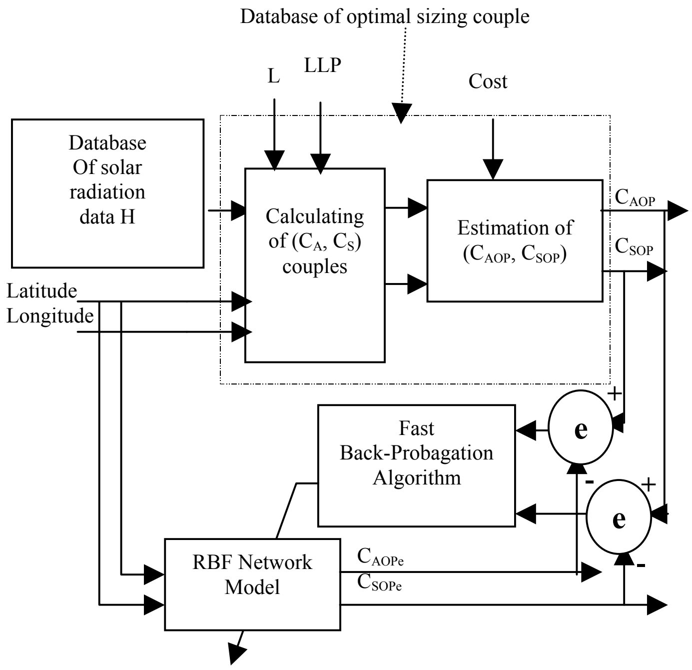

Fig.5. Diagram block of developed model

6. RESULTS AND VALIDATION

Once a satisfactory degree of input-output mapping has been reached, the RBF network training is frozen and the set of completely is an unknown test data that was applied for validation. After simulation of many different structures, we found that the best performance is obtained with a one hidden layer with 12 neurons. The best model is validated by comparison between identified results and actual calculated values for the optimal sizing couples that is shown in figure 6. We observe that there is almost a complete agreement between the two series.

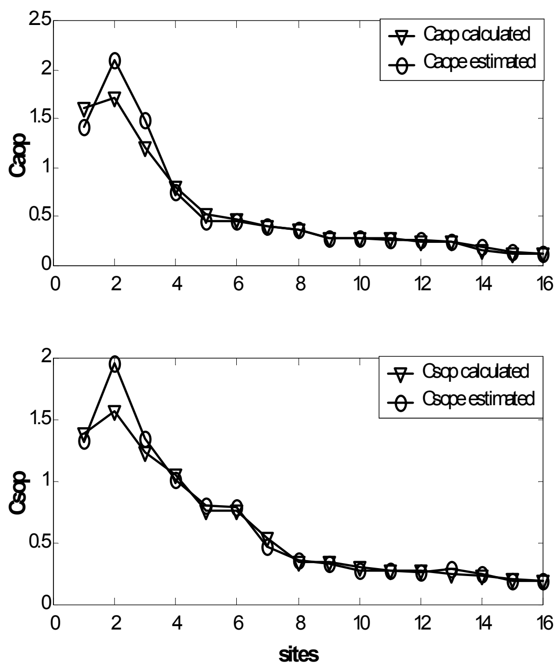

Fig.6. Comparison between calculated and identified of the optimal sizing couples

Table 2 displays the statistical features (mean, variance and correlation coefficient) between the calculated couples and those identified by our model, it is found that there is no significant difference between the identified and the measured parameter from the statistical features point of view. The correlation coefficient obtained for the validation data set is 97.9% for C_{AOP} and 98.9 for C_{SOP}. In this respect, the closer to unity these values are the better the prediction accuracy.

Table. 2 Comparison between actual and identified results

	Statistical tests			
Optimal Sizing Couples	Calculated Mean	Estimated Mean	Variance	Correlation coefficient (%)
C_{AOP}	1.076	1.051	0.270	97.9
C_{SOP}	1.135	2.112	0.226	98.9

7. EXAMPLE OF SIZING

In this part, we present an example in order to illustrate how one uses this model to determine the PV-array area and useful capacity. Firstly, you were to give in input of the model the geographical coordinate of site. Then, from the model we obtain the C_{AOP}, and C_{SOP}, for given consumption L, Eq.(2) allows to calculate the A_{PV} and the C_U, the number of solar modules and batteries, which are determinate according to unit dimension of module and the storage capacity of the battery. Table 3 the shows the results obtained for some sites going the north towards the south of Algeria.

Table 3. Example of sizing

Sites		LLP=1%, L=2KW/Day			
Latitude (Deg.)	Longitude (Deg.)	C_{AOP}	PV-array Area A_{PV} (m^2)	C_{SOP}	Useful accumulator capacity C_U (KW)
36	0	1.92	7.8049	1.74	2.87
35	8	2.59	8.0000	2.46	3.14
34	2	1.98	6.2051	1.85	2.48
33	-1	1.25	3.3333	1.52	2.10
32	9	0.96	2.1224	1.31	1.52
31	-4	0.95	1.9200	1.29	1.52
30	-3	0.90	1.4815	0.97	1.08
29	5	0.87	1.2857	0.86	0.70
28	-2	0.78	0.9655	0.83	0.70
27	10	0.78	0.9333	0.78	0.62
26	2	0.77	0.9180	0.78	0.56
25	-2	0.77	0.7742	0.76	0.56

8. CONCLUSION

The objective of this work is to train the RBFN to learn the prediction and modeling of the optimal sizing couples of stand-alone PV system with a minimum of input data for any locations in Algeria. Once trained, the RBFN estimates these couples faster. The validation of the network was performed with unknown sizing couples, which the network has not seen before. The ability of the network to make acceptable predictions even in an unusual day is an advantage of the present method. It should be stressed that the training of the network required about 1 minute on a Pentium III 800MHz machine. The prediction with correlation coefficient of 98 % was obtained. This accuracy is well within the acceptable level used by design engineers. The methods of sizing PV system (empirical, analytical, numerical and hybrid) previously allows to estimate the sizing of PV system for one given site, and requires the availability of several parameters such as the daily solar irradiation data, altitude, longitude, the load, the characteristics of stand alone PV system, the inclination of the panels and to take very much computing time for estimation of optimal couple. On the other hand, the model that we developed allows estimating the PV-array area and the storage capacity from a minimum input data (altitude, longitude) based on the optimal sizing couples and does not take much time for simulation. The advantage of this model is to estimate of the PV-array area and the storage capacity in any site in Algeria particularly in isolated sites, where the global solar radiation data is not always available. The results have been obtained for Algerian meteorological data, but the methodology can be applied to any geographical area.

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